Machine Learning for Soft Robot Sensing and Control: A Tutorial Study

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***Abstract*—Developing feedback controllers for robots with embedded sensors is challenging and typically requires expert knowledge. As machine learning (ML) advances, the development of learning-based controllers has become more and more accessible, even to non-experts. This work presents the development of a tutorial to educate non-roboticists about ML-based sensing and control in cyber-physical systems using a soft robotic device. We demonstrated this by creating a recurrent neural network-based closed-loop force controller for a soft finger with embedded soft sensors. Our hypothesis is validated in a 2.5-hour workshop session for students with no prior knowledge of robot control. This work serves as a tutorial for participants aiming to experience and perform a general benchmark for soft robot control tasks, with little or even no expertise in robotics.**

I. Introduction

Soft robots are becoming prevalent in developing safe, flexible and robust robotic systems [1], [2]. Soft robotic devices with embedded soft sensors is revolutionizing the field of health monitoring, industrial manipulation and human-machine interaction (HRI) due to its highly compliant and omni-directional features [3], [4]. However, modelling soft sensors is a challenging problem because of its visco-elastic properties that result in high non-linearity, hysteresis and delayed response [5], [6].

The design, fabrication, and modelling of soft robotic devices and sensors is a recent field with numerous challenges, especially because of its multidisciplinary nature [7]. The integration of soft sensors and control strategies in a soft-bodied robot necessitates advanced expertise in multidisciplinary researches, ranging from material science, robotics, and artificial intelligence. This multidisciplinary nature can help foster in-depth collaborations, but can also act as a deterrent for non-experts to join the field. Soft material engineering, for example, necessitates researchers with a material science background. However, young researchers with a purely material-based background may know little about robotics and vice versa. Simulation-based and hands-on tutorials are one of the ways to provide training and education to researchers coming from different backgrounds [8]–[11].

This paper presents the development of a tutorial on learning-based control of soft robots with embedded sensors and its subsequent validation through a workshop tutorial. The tutorial aims to act as an educational toolkit for non-roboticists and students to gain knowledge on the field of soft robotic sensing and control, particularly using learning-based approaches. The tutorials include a simulation model as well as an experimental setup. The tutorial's objective is to construct a learning-based state estimator to provide closed-loop force control for a soft finger with embedded soft sensors. Both the simulated and real-robot platforms will be used to test the control strategy. We hypothesize that combining both the physical experimental setup and its data-driven replication can improve non-experts' robotics knowledge and expertise. Our hypothesis is validated by a physical workshop with statistics from participants survey. During the workshop, the proposed tutorial has been followed by 20 participants with a wide background. The tutorial teaches the participants how to generate training data, tune the parameters for both the machine learning model and the controller to obtain an accurate one-axis force tracking controller. Based on the feedback of the survey, we observe that the tutorial has indeed helped the participants to improve their expertise in the field and conclude that the tutorial can serve as an effective tool for soft robotics education and training.

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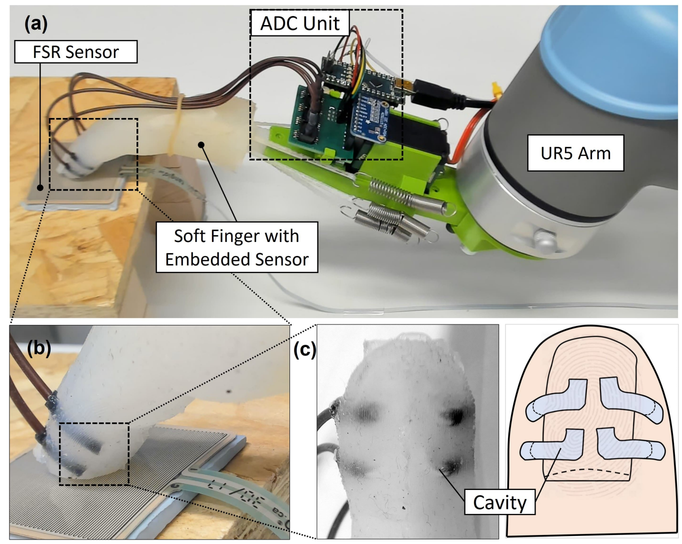

Fig. 1. Soft robotic platform used for the tutorial. (a) The anthropomorphic soft finger; (b) The soft finger interacting with the ground-truth FSR sensor for learning; (c) Design of the soft sensor based on pressure variations inside the fingertip cavities.

II. Materials and Methods

The demonstrator of the tutorial includes a robotic platform and learning-based controller. The experimental setup consists of the robotic arm (UR5, Universal Robots) enabling control of the position and orientation of the wrist, as well as the soft finger equipped with tactile sensors measuring the contact pressure. The learning-based controller transforms multi-dimensional tactile signals to actual contact forces in meaningful physical units.

A. Sensorized Finger

The anthropomorphic finger, as shown in Figure 1(a), consists of 3D printed skeleton with tendons and silicone-casted artificial skin (Ecoflex 00-30, Smooth-On Inc.). The characteristic of the silicone layer resembles the natural dynamics of the human flesh, which in turn, stabilizes the interaction by absorbing the impact energy with the environment.

To measure the contact forces of the interaction, four air chambers were cast at the tip of the anthropomorphic finger and connected to NXP MPXH6300AC6U pressure sensors via elastic hoses. The force exerted against the exterior surface is measured using a FSR sensor. Figure 2(a) demonstrates the finger-object contact and the process of finger deformation. Meanwhile, the pressure in the embedded cavity/chambers changes according to the local deformation at the contact point. Despite the high non-linearity of a soft fingertip, Figure 2(b) demonstrates the pressure signals of the contact, as well as corresponding force readings collected by the FSR sensor. A recurrent neural network such as Long Short Term Memory (LSTM) allows to development of an accurate and robust state estimation model of the time-variant embedded soft sensors [12]. Furthermore, the orientation of the fingertip with respect to the contact surface can be inferred from the pressure signals, as the pressure distribution in chambers changes due to its pose.

The pressure signals are amplified and converted to digital ones using a four-channel ADC board with programmable gain (ADS1115). The amplified digital signal is then passed to the microcontroller (Arduino Nano) through the I2C communication channel. Likewise, the FSR sensor was directly connected to the same microcontroller to measure an analog signal from the FSR sensor.

B. Learning-based Control Framework

The Learning-based controller consists of two components. The former component is a LSTM-based model that converts the noisy pressure signals with a possible sensor drift into contact forces. The latter one is a PID controller that adjusts the vertical translation of the robotic wrist to maintain a certain level of the contact force. Therefore, the complete procedure comprises of three steps, i.e., sampling the training data, training LSTM model, and tuning a closed-loop controller.

Prior to the fine-tuning the controller's parameters, 20 batches of data are obtained by making the finger randomly press the FSR surface, during which both force and pressure information are collected. To sense and perceive the external environment, it is necessary to comprehend the relationship between force and tactile information on the fingertip. A mapping tool that models the time-variant non-linearity of soft tissue during its impulsive contact with objects would

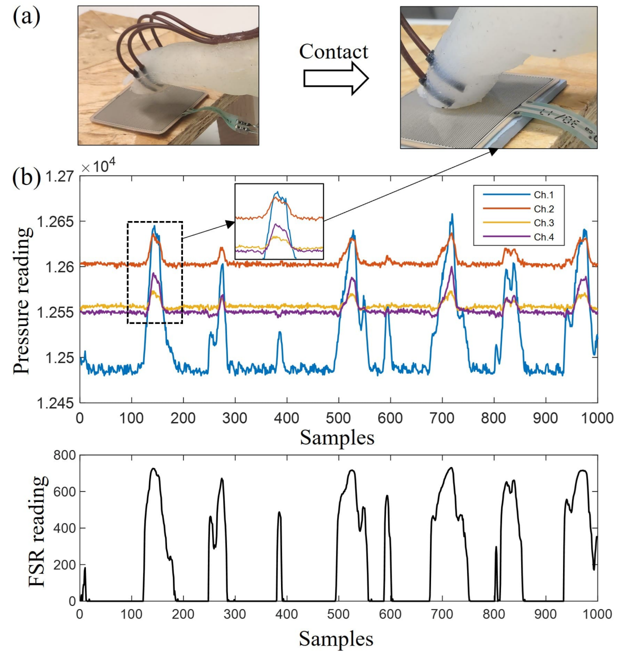

Fig. 2. Raw response of the soft sensors to contact (a) Before and after the contact; (b) Tactile signals (top) and the corresponding force (bottom).

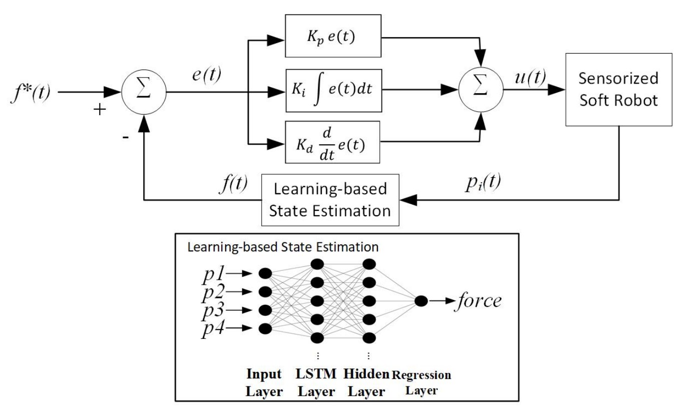

Fig. 3. Schematic of the learning-based closed-loop force control architecture.

fulfill the perception modelling. As one type of RNN, the Long Short-Term Memory network (LSTM) is renowned for its high performance in dealing with the vanishing gradient problem in traditional RNNs and the ability in learning long-term dependencies [13]. The collected data is fed to the LSTM network to model the relation between the sensory observations and force. Finally, a closed-loop proportional controller has been developed to regulate the force exerted onto the surface. By defining a the target force and removing the FSR sensor, the model enables approximation of contact force, which imitates the proprioception. Using real-time tactile data from the fingertip, the UR5 arm can dynamically adjust its vertical position. The overall design of the learning-based controller is depicted in Figure 3, where $f^*(t)$ represents the reference group of force and $p_i^*(t)$ is the corresponding pressure signal. The overall control function is as follows:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{d}{dt} e(t) \tag{1}$$

where

$$e(t) = \sum_{i=1}^{4} [\lambda_i (p_i^*(t) - p_i(t))] \tag{2}$$

The PID coefficients are denoted by K_p, T_i and T_d, respectively. For the tutorial participants are required to tune these parameters to achieve an accurate and robust control of the finger, including minimizing static error and realizing rapid system response, during which time they can understand how each parameter affects robot performance. The weight of pressure perception load on each embedded sensor is specified by the coefficients λ_i that subject to $\sum_{i=1}^{4} \lambda_i = 1$.

III. Simulation Study

The machine learning based closed-loop control strategy is validated in simulation prior to its physical implementation. By exploiting a state-of-the-art multi-body dynamics simulation platform, a data-driven soft robot finger with embedded strain sensors is established to execute a sensing and perception experiment. The learning objectives of the simulation tutorial aims to help the participants to:

- Model soft elements and sensors on an anthropomorphic finger.
- Perform state estimation using regression techniques including linear, machine learning and deep learning based approaches.
- Realize the control of end-effector contact dynamics using feedback control strategy.

A. Modelling of Finger and Sensor

The finger is geometrically built as four elements that represent the finger bones. The ligaments are modelled as three revolute joints that enable the relative angular displacement between each pair of elements. The actuation of the wrist-driven finger is defined by the motion control of one prismatic primitive that allows the movement of the whole finger in the z-axis (see Figure 4). The embedded sensing is performed in a data-driven manner. Nine strain sensors, using the Wheatstone Bridge configuration for measuring resistance, are embedded on the fingertip for sensing and perception.

In accordance with the the three phases in physical experimentation, the objective of the machine learning in the virtual prototype is to create a state estimator to relate the strain measurements from the gauges embedded in the finger to contact force between the finger and the platform. Primarily, the data-collection stage of the state estimator has been performed using a data-driven approach, during which the finger is actuated to move up and down in the z-axis with a random walk function as:

$$z(k+1) = z(k) + v_r * \Delta t \tag{3}$$

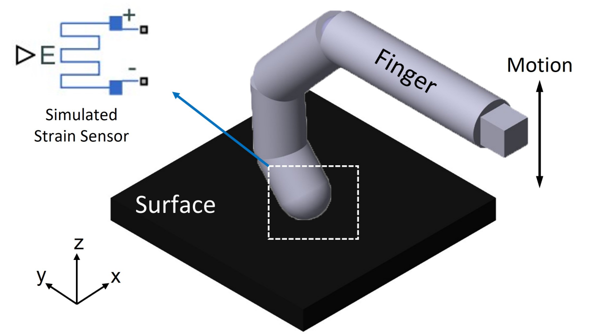

Fig. 4. Simulated prototype of the underactuated finger with strain sensor in Matlab Simscape.

where the random velocity is a normally distributed with variance σ_z:

$$v_r \sim N(0, \sigma_z^2) \tag{4}$$

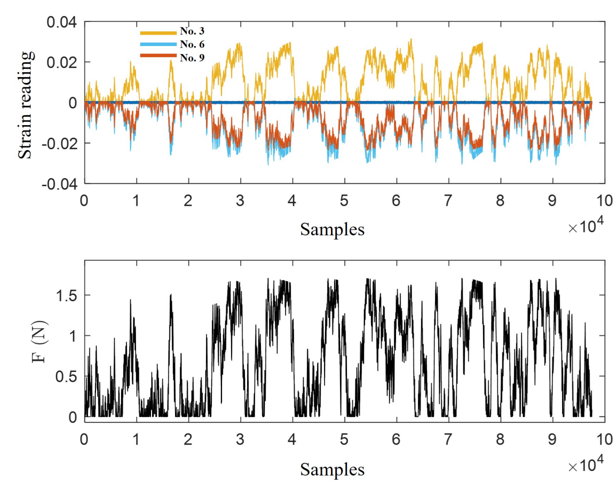

Fig. 5. Strain sensor data vs. ground-truth force in simulation.

In simulation, we perform the sensing and perception of soft sensorized finger and examine the sensor responses created in the multi-body dynamics simulation. Figure 5 illustrates how the strain sensor data is varying versus the ground-truth force samples in simulation, from which it can be seen that 3 channels of strain sensors out of 9 are significantly related to the force variation.

B. Correlation Analysis

In order to have an in-depth understanding of how the tactile sensing data is correlated with the ground truth force, the correlation between the sensor responses and tip force has been analyzed. Figure 6(a) depicts how the normal force on the surface changes with 9 different strain sensors. It can be seen that the force is highly related to sensor 3, 6 and 9, with absolute correlation coefficients over 0.98. The entire correlation matrix between 9 sensors and force is illustrated by the heatmap in Figure 6(b), from which it can be concluded that there is a positive correlation between force and sensor 3 but negative correlation with sensor 6 and 9. This is consistent with the results shown in Figure 5 and 6(a).

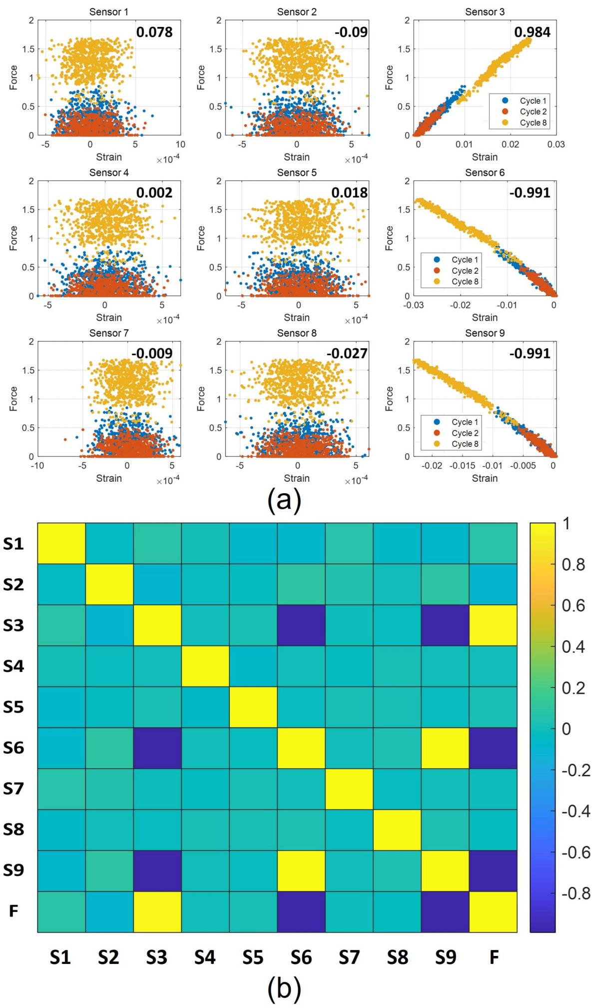

Fig. 6. Correlation analysis between raw strain sensor data and force sensor for the simulated system. Drift in the sensor data is evident through repeated cycles.

C. Force-tracking Performance

A regression model based on an LSTM network has been utilized to build a state estimation model that relates the strain sensor readings to the contact force. The machine learning model trains the collected data from the data-driven framework and predicts the force exerted onto the surface. Then, a closed-loop architecture based on PID control has been established to achieve the control of the wrist-driven end-effector (i.e., $u(t)$, z-axis motion of finger). Finally, the data-driven sensorized finger is employed to perform a force tracking task. A square wave function is set as the benchmark signal and the participants are supposed to tune the controller parameters to achieve an accurate and rapid tracking of desired force with the consideration of static steady error and overshoot. Figure 7 illustrates the force-tracking performance with a tuned machine learning model and closed-loop controller.

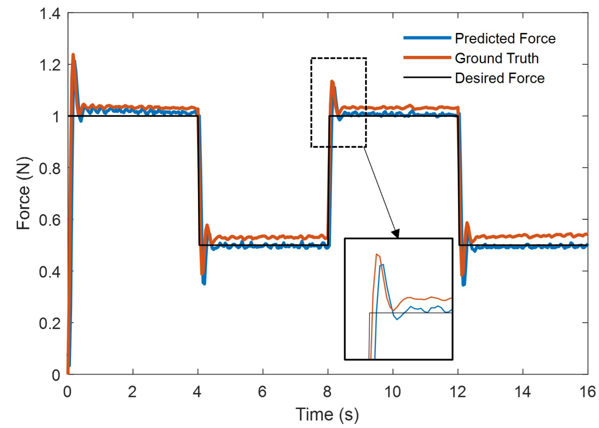

Fig. 7. Force tracking performance with the simulated soft robot using embedded strain sensors.

IV. Workshop and Participants Survey

A. Workshop Implementation

The hypothesis has been validated through the workshop titled "Machine learning for modelling and control of Soft Robots" on the 1st International Winter School on Smart Materials for Soft Robots (12-17 December 2021, Cambridge, UK). The tutorial was distributed among 4 groups of 20 participants from varying background. After the workshop, we performed a survey study on each participant about how they rated the tutorial, and from the 20 participants we received 18 feedback forms. Table I lists the statistics of the background of participants involved in the workshop.

TABLE I
Background statistics of the participants.

	Statistics	
Gender	Male (77.8%)	Female (22.2%)
Age	22-31 years old	
Expertise	Robotics (55.6%)	Material (44.4%)
Qualification	Postgraduate (100%)	
Institute	10 universities from 12 countries	

The workshop using the proposed tutorial consisted of three stages (see Figure 8). Before the practical implementation, all participants were given a lecture about the general design principle and theory of the machine learning algorithm for tactile sensing and control, together with safety rules and manipulation guidance. After that, participants were asked to perform the modelling and control of the soft finger in simulation. This is to leave the participants a preliminary impression on how tactile sensing and control can be performed in a virtual system without having to worry about setting up the hardware platform.

The final phase is the physical experimentation on the soft robot. Participants were asked to tune parameters of both

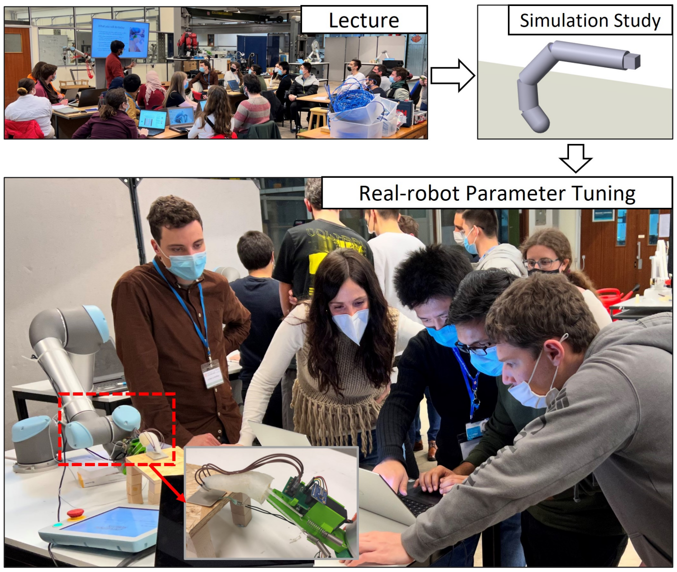

Fig. 8. Workflow of the workshop.

the machine learning model and PID controller. Tuning the hyperparameters of machine learning algorithms help participants to understand how each of these parameters affects the performance of the mapping between the sensory data and force, while configuring the controller helps to extend their knowledge and skills towards developing a classic control strategy. The immersive learning and practice not only help the participants, especially for those non-experts in robotics, to rapidly develop the basic skills in robot design, fabrication and control, which are necessary for design intelligent robotic systems, but also understand how Artificial Intelligence (AI) is powerful in dealing with abundant multi-dimensional sensory data in robot sensing and perception. Finally, a competition targeted to optimal force tracking was held among the groups. Figure 9 illustrated the training progress of the machine learning model and the prediction of force versus ground truth force of the prize-winning group. From which it can be seen that the LSTM-based machine learning framework realizes a precise state estimation of the sensorized finger with the mean error $< 0.1N$.

B. Survey Study

In order to study the effectiveness of the tutorial for researchers with little or even no experience in robotics, a survey was held. Based on the feedback, we quantitatively studied the value of the conducted tutorial.

The participants were asked to prescribe their rating of the simulation study and the experimental study. In particular, they were asked to rate the tutorial in a 1-7 scale. Figure 10(a) depicts the grading statistics from 18 participants for the simulation based part and the real-robot based counterpart in the tutorial. Let G denote the array of marks prescribed by all participants, with G_i denoting the score evaluated by the ith participant and G_{max} and G_{min} denoting the highest and

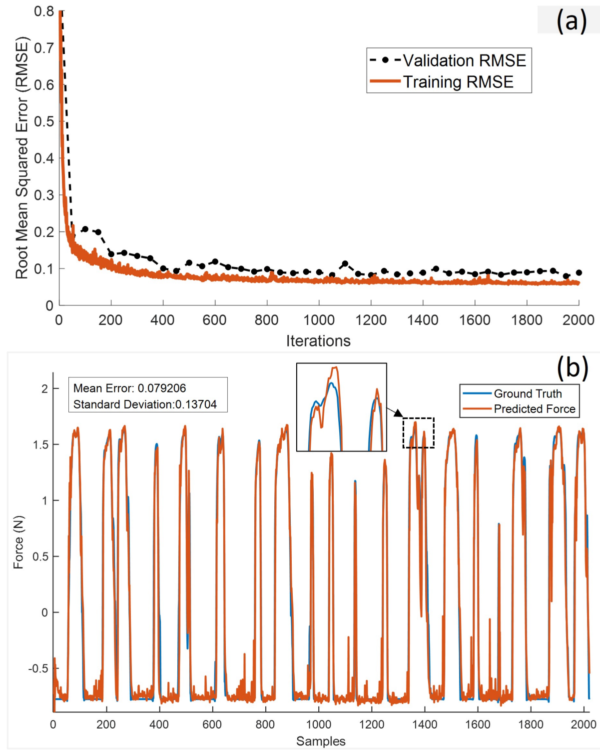

Fig. 9. Learning performance of state estimation task. (a) LSTM training progress; (b) LSTM prediction performance on the validation set after training.

lowest scores, respectively. A satisfaction index SI is defined as:

$$SI = \frac{\sum_{i=1}^{n} G_i - n \cdot G_{min}}{n(G_{max} - G_{min})} * 100\% \qquad (5)$$

where n denotes the number of participants. Therefore, it can be calculated that the satisfaction index for the two components in the tutorials are $SI_{sim} = 49.1\%$ and $SI_{real} = 56.5\%$. This means that neither the simulation nor the experimental tutorial passes the cut-off scores (60%). In contrast, 83.3% of the participants agreed that the combination of both extends their general knowledge and improve their skills in robotics (right pie-chart in Figure 10(b)). Furthermore, 72.2% of the trainee showed great interests in applying the concepts learned in the tutorial for their future researches.

Based on the simulation study as a prior, the participants built an early understanding of the general concept of the soft robot sensing and control using learned models. After that, they were asked to transfer and implement the skills learned from simulation to a real-robot platform. The combination of both simulation and physical experimentation give participants insights into real-world problems, and find the potential solutions to these problems. The complementary experiments would also serve as an educational benchmark tutorial for participants to learn how skills and optimizations implemented in simulation can be transferred to a real hardware set with minimized reality gap (i.e., sim2real transfer [14]).

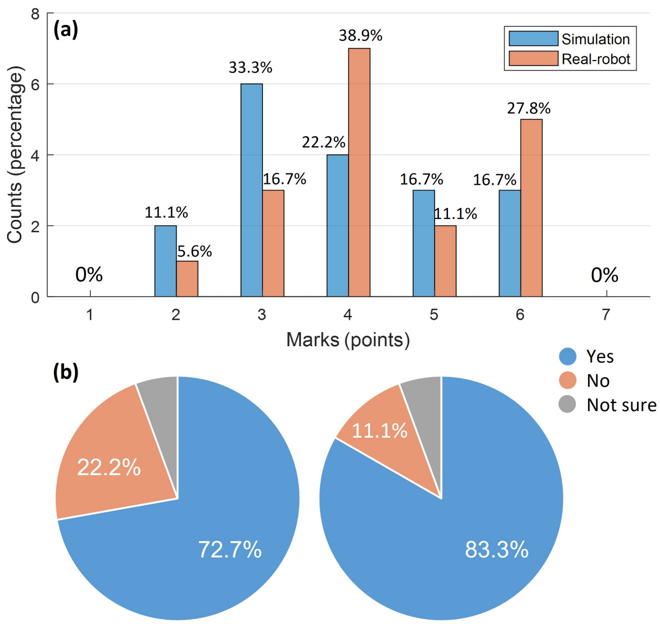

Fig. 10. Participants feedback analysis. (a) Histogram of participants' rating towards the simulated and real-robot tutorials. (b) Pie-charts about trainees willingness to apply the learned knowledge in future researches (left) and if the complementary experiments extend their skills (right).

V. Discussion & Conclusion

This paper presents an educational tutorial for using machine learning for soft robot sensing and control. The tutorial consists of both a simulated part and its full-replication in a physical experimental setup. An anthropomorphic finger with embedded tactile sensors is used as the experimental platform. A machine learning approach based on RNN is used as the state estimator for closing the force control loop. The tutorial aims to help young scientists, especially those from non-robotics background, to improve their knowledge in the rising field of soft robotics.

The tutorial is validated through a 2.5-hour workshop session. With the proposed tutorial, the participants are able to (1) understand how machine learning helps to build a model-free approach to process tactile information (2) develop intuition behind the tuning of various control and training parameters (3) cultivate team-working skills with in-depth collaboration with researchers from multiple disciplines (4) understand the challenges in sim2real transfer and (5) develop a closed-loop force controller for a general soft robot with embedded soft sensors. Over 80% of the participants had indicated their skills in robotics have been improved after the workshop.

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References

[1] D. Rus and M. T. Tolley, "Design, fabrication and control of soft robots," *Nature*, vol. 521, no. 7553, pp. 467–475, 2015.

[2] S. Kim, C. Laschi, and B. Trimmer, "Soft robotics: A bioinspired evolution in robotics," *Trends in biotechnology*, vol. 31, no. 5, pp. 287–294, 2013.

[3] M. Amjadi, K.-U. Kyung, I. Park, and M. Sitti, "Stretchable, skin-mountable, and wearable strain sensors and their potential applications: A review," *Advanced Functional Materials*, vol. 26, no. 11, pp. 1678–1698, 2016.

[4] H. Wang, M. Totaro, and L. Beccai, "Toward perceptive soft robots: Progress and challenges," *Advanced Science*, vol. 5, no. 9, p. 1 800 541, 2018.

[5] T. George Thuruthel, P. Gardner, and F. Iida, "Closing the control loop with time-variant embedded soft sensors and recurrent neural networks," *Soft Robotics*, 2022.

[6] T. G. Thuruthel, J. Hughes, A. Georgopoulou, F. Clemens, and F. Iida, "Using redundant and disjoint time-variant soft robotic sensors for accurate static state estimation," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 2099–2105, 2021.

[7] G. Bao, H. Fang, L. Chen, *et al.*, "Soft robotics: Academic insights and perspectives through bibliometric analysis," *Soft robotics*, vol. 5, no. 3, pp. 229–241, 2018.

[8] R. R. Murphy, "" competing" for a robotics education," *IEEE Robotics & Automation Magazine*, vol. 8, no. 2, pp. 44–55, 2001.

[9] K. Nagai, "Learning while doing: Practical robotics education," *IEEE Robotics & Automation Magazine*, vol. 8, no. 2, pp. 39–43, 2001.

[10] K. S. Rawat and G. H. Massiha, "A hands-on laboratory based approach to undergraduate robotics education," in *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004*, IEEE, vol. 2, 2004, pp. 1370–1374.

[11] J. M. Gomez-de-Gabriel, A. Mandow, J. Fernandez-Lozano, and A. J. Garcia-Cerezo, "Using lego nxt mobile robots with labview for undergraduate courses on mechatronics," *IEEE Transactions on Education*, vol. 54, no. 1, pp. 41–47, 2010.

[12] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[13] R. Pascanu, T. Mikolov, and Y. Bengio, "On the difficulty of training recurrent neural networks," in *International conference on machine learning*, PMLR, 2013, pp. 1310–1318.

[14] H. Wang, T. Howison, J. Hughes, A. Abdulali, and F. Iida, "Data-driven simulation framework for expressive piano playing by anthropomorphic hand with variable passive properties," 2022.